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Efficient Learning in Team Games

A Coordination-Competition Dilemma

By

Luca Carminati

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Supervisor(s):
Prof. Nicola Gatti, Supervisor
Prof. Marcello Restelli, Tutor

Doctoral Examination Committee:
Prof. Cesa-Bianchi Nicolò , Referee, University of Milan
Prof. Ferraioli Diodato, Referee, University of Salerno
Prof. Andrea Celli, Bocconi University
Prof. Stefano Moretti, Paris Dauphine University
Prof. Stefano Di Carlo, Politecnico di Torino

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Luca Carminati
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Efficient Learning in Team Games

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A significant challenge in the field of Artificial Intelligence lies in addressing the sequential decision-making processes of multiple rational agents operating concurrently within a shared environment. *Algorithmic Game Theory* provides a compelling framework combining a rigorous game theoretical approach with a computational one; the main questions it addresses are to characterize equilibrium behavior and to compute optimal strategies efficiently. Significant results have been obtained in the well-understood two-player zero-sum setting with imperfect information. Experimentally effective techniques apply learning procedures to compute approximated optimal strategies, obtaining superhuman performance in large-scale games such as Poker or Diplomacy.

On the other hand, only a small amount of progress has been made in dealing with a larger number of players. This dissertation focuses on the *team* setting with imperfect information where two teams with multiple players have opposite utilities. This setting presents a coordination-competition dilemma. On the one hand, players desire to play simple strategies whose actions reveal their private information to team members; this would allow more effective cooperation. On the other hand, revealing private information increases the risk of exploitation by opponents. The tension between these opposite incentives is the common thread throughout the dissertation.

While previous approaches navigate the complexity with a progressive expansion of the correlated strategy space of each team, we reformulate the problem as an equivalent two-player zero-sum game between team coordinators. This formulation relies on novel efficient constructions. We can therefore adopt the scalable learning approaches developed for the two-player zero-sum setting, which can be adapted to better exploit the structure of our representations. We apply this approach to propose novel efficient representations for *adversarial team games*, where the teams are known before the start of the game, and, therefore, pre-play coordination allows team members to jointly sample their strategies. This representation also allows the definition of a *team-maxmargin* algorithm for solving subgames rooted at arbitrary points of the game. We also extend our analysis of team games to a novel setting called *hidden-role* games. The particularity of this setting is that teams are sampled randomly at the start of the game, and players can usually communicate to coordinate and deceive the others, as seen in games like *Mafia* and *Avalon*. Experimental results show that our approaches enable faster and more scalable computation of equilibrium strategies.